Optimized Cooperative Localization Technique Based on Linear Intersection over Wireless Sensor Networks

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Abstract

Localization is one of the significant techniques in wireless sensor networks. The localization approaches are different in several applications. Localization offers geographical information for managing the topology. In this paper, we propose optimized cooperative localization technique based on trilateration, multilateration and linear intersection. The approach reduces the error rates, communication cost and energy consumption for maintaining the high accuracy. Furthermore, the approach is implemented for controlling air craft system to avoid the landing and takeoff delays. To demonstrate the strength of the approach, we used network simulator ns-2 to validate the estimation errors, computational latency, energy consumption and error tolerance. Based on the simulation results, we conclude that the presented approach outperforms other existing cooperative scheduling approaches in terms of accuracy, mobility, consumed power.

I. Introduction

Wireless sensor networks (WSNs) consist of small size sensor nodes that involve monitoring of the physical environment. Each sensor node has detecting capabilities to collect and process the sensed data for accomplishing a collective goal [1-2]. Mobile sensor networks (MWSNs) are a special kind of WSNs in which mobility performs prominent role in the accomplishment of the application. In recent years, mobility became one of the challenging research areas for the WSN community. Although WSN organizations were never projected to be completely static, mobility was primarily regarded as having numerous challenges that required to be handled, including coverage, connectivity, and energy consumption, among others. However, the latest studies have been presenting mobility in a more auspicious light [3]. Rather than confusing these issues, it has been proven that the introduction of mobile sensor nodes can solve some of these issues [4-5]. In addition, mobility empowers the sensor nodes to track and target moving wonders such as vehicles, chemical clouds, and packages [6-7].

One of the most important challenges for MWSNs is the necessity to support localization. In order to comprehend the sensor data in an altitudinal perspective, or for suitable triangulation through a sensing region, sensor node location must be determined. Because sensor nodes may dynamically be arranged (i.e., plummeted from an aircraft), or may adjust location during run-time (i.e., when incorporated with shipping container), there may be no way of determining the position of each node at the specific period. For fixed WSNs, this is not as much of a problematic because once sensor node location have been identified, they are expected to change. From the other side, mobile sensor nodes dynamically assess their locations that take time and consume the energy, and also wastes other resources required by the sensing application. Additionally, localization approaches offer correct positioning information that cannot be activated by mobile sensors, because they normally involve centralized processing, which take longer time to run regarding the situation or network topology that do not employ to dynamic networks.

This paper introduces a mobility model to target the location of sensor nodes based on the scheduling approach. Determining the location of mobile sensor nodes is highly critical and also very challenging for several applications. The model helps to calculate the distance and location of moving sensor nodes with high accuracy. This approach outperforms other existing cooperative scheduling approaches in terms of accuracy, mobility, computation power, and beacon percentage and node density. In addition, existing approaches lack the mobility support and having the accuracy issue.

II. System Model Based on Scheduled Cooperative Technique

The sensor nodes are capable to offer different sensing information. The application level sensing jobs are done with connection of multiple sensing features [8]. The system model scenario should be flexible to support projected tasks. Thus, our designed system model scenario supports air-traffic control using two types of devices;

sensor nodes and legacy radar. The sensor nodes are used to track the air-traffic control system. We have used particular type of sensor nodes that are Bluetooth-enabled sensor nodes (BTnode rev3) that is a self-directed prototyping platform. This platform is supported with microcontroller, Bluetooth radio and ZigBee.

The Bluetooth radio is used for handling the airplane when landing on and taking off and used for short distance. However, BT node sensors have another support of ZigBee that handle the airplanes at further distances and costumed for thousands sensor nodes based on multilateration approach.

If we need to locate the airplane at the shortest distance then Bluetooth radio feature is activated whereas ZigBee is active for long distance. Sensor BT node has complete support for distributed wireless sensor networks, wired networks, wireless networks and ad-hoc networks [9]. The designed system model scenario comprises of exterior wireless sensor (EWS) that uses seismic sensor, lightning sensor and infrasonic sensor and having functionalities of iMote2 sensors as deployed in experiment [10].

EWS is deployed to track the airplane and respond to Air traffic control (ATC). The ATC is a service handled by EWS which directs the aircraft on the ground and through controlled airspace, and can provide advisory support to aircraft in non-controlled airspace. The primary goal of this system model is to use scheduled based cooperative technique to track the planes. This also prevents collisions, establishes and accelerates the flow of traffic, and gives the information and other assistance to pilots. The system model is depicted in Figure 1.

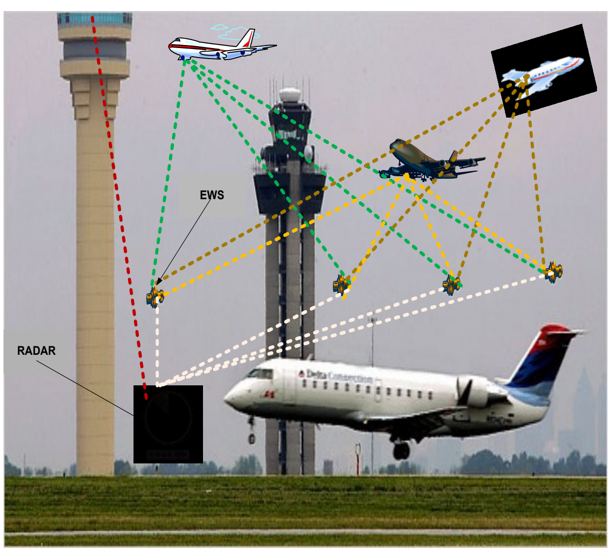

Figure 1: Scheduled based cooperative localization tracking of air traffic control system

A. Scheduled Based Localization

Our scheduled based localization approach is based on the distance measurement. In this approach, each unidentified node communicates with beacon nodes in order to obtain identified distance and location information for localization. The distance information requires manipulating capability of node to measure. The distance measurement process is used that is Received Signal Strength Indicator (RSSI), Time of Arrival (TOA), Time Difference of Arrival (TDOA), and so on. Unidentified nodes decide their positions locally using trilateration and multilateration.

B. Trilateration Formulation

Trilateration is used to accumulate the intersection of three shares or circles. Assume ‘J’, ‘K’ and ‘L’ are three beacon nodes with identified locations (aJ, bJ), (aK, bK), (aL bL), respectively. ‘M’ is the unidentified node with expected location (a,b). Let us take r_J, r_K, r_L as distances between M and J, K, L shown in Figure 11. Thus, it can be illustrated as follows:

$$\begin{cases} \sqrt{(a-a_J)^2 + (b-b_J)^2} = r_J \\ \sqrt{(a-a_K)^2 + (b-b_K)^2} = r_K \\ \sqrt{(a-a_L)^2 + (b-b_L)^2} = r_L \end{cases} \qquad (1)$$

The location of ‘M’ is obtained from equation system (1) and can be written in matrix form as given below: (2)

$$\begin{bmatrix} a \\ b \end{bmatrix} = \begin{bmatrix} 2(a_J \_ a_L) & 2(b_J \_ b_L) \\ 2(a_K \_ a_L) & 2(b_K \_ b_L) \end{bmatrix}^{-1}$$

$$\begin{bmatrix} 2(a_J^2 \_ a_L^2 + b_J^2 - b_L^2 + r_L^2 - r_J^2 \\ 2(a_K^2 \_ a_L^2 + b_K^2 - b_L^2 + r_L^2 - r_K^2 \end{bmatrix} \qquad (2)$$

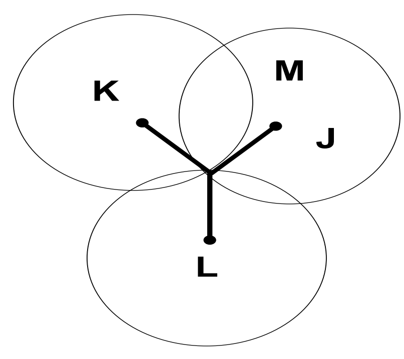

Figure 11: Schematic diagram of trilateration

C. Multilateration Formulation

More than three beacon nodes are used to identify the location of one unidentified node. For example a_1, a_2, a_3, . . ., a_n are beacon nodes with locations (m_1 , n_1) , (m_2 , n_2), …, (m_n , n_n) respectively. The distance between unidentified node 'Z' and beacon nodes can be expressed as: $r_1, r_2, r_3, \ldots, r_n$. Thus, the location (m, n) can be illustrated as follows.

$$\begin{cases} (m_1 - m)^2 + (n_1 - n)^2 = r_1^2 \\ \quad . \\ \quad . \\ \quad . \\ (m_n - m)^2 + (n_n - n)^2 = r_n^2 \end{cases} \tag{3}$$

By subtracting (n-1) from equation (3) to get the following equation.

$$\begin{cases} m_1^2 - m_n^2 - 2(m_1 - m_n)m + n_1^2 - n_n^2 - \\ \quad 2(n_1 - n_n)n = r_1^2 - r_n^2 \\ \quad . \\ \quad . \\ \quad . \\ m_{n-1}^2 - m_n^2 - 2(m_{n-1} - m_n)m + n_{n-1}^2 - n_n^2 - \\ \quad 2(n_{n-1} - n_n)n = r_{n-1}^2 - r_n^2 \end{cases} \tag{4}$$

Thus, equation (4) can be illustrated as GY= n, where

$$G = \begin{bmatrix} 2m_1\left(\quad m_n\right) & 2n_1\left(\quad n_n\right) \\ 2\left(a_K \quad a_L\right) & 2b_K\left(\quad b_L\right) \end{bmatrix}^{-1} \begin{bmatrix} 2(a_J^2 \_ a_L^2 + b_J^2 - b_L^2 + r_L^2 - r_J^2 \\ 2(a_K^2 \_ a_L^2 + b_K^2 - b_L^2 + r_L^2 - r_K^2 \end{bmatrix}$$

$$G = \begin{bmatrix} 2(m_1 - m_n) \; 2(n_1 - n_n) \\ . \\ . \\ . \\ 2(m_{n-1} - m_n) \; 2(n_1 - n_n) \end{bmatrix}, n$$

$$= \begin{bmatrix} m_1^2 - m_n^2 + n_1^2 - n_n^2 + r_n^2 - r_1^2 \\ . \\ . \\ . \\ m_{n-1}^2 - m_n^2 + n_{n-1}^2 - n_n^2 + r_n^2 - r_{n-1}^2 \end{bmatrix}, Y = \begin{bmatrix} m \\ . \\ . \\ . \\ n \end{bmatrix} \tag{5}$$

The location of unidentified node 'Z' can be determined using least mean square estimation.

$$Y = (G^S\, G)^{-1}\, G^S n \tag{6}$$

Multilateration improves the localization and also reduces the overhead and depicted in Figure 2. In Figure 2, the beacon nodes periodically transmit the signals to help unidentified nodes for location discovery. Once unidentified node gets signals from beacon nodes then it measures the distance using location information technique. This approach has two key benefits; first, each unidentified node in wireless sensor networks calculates its location independently without translating the all information to selected place for location calculation. The second is to have a capability of the unidentified node to listen to two or multiple beacon signals during beacon period without transmitting radio signal. These two features decrease the communication overhead of nodes.

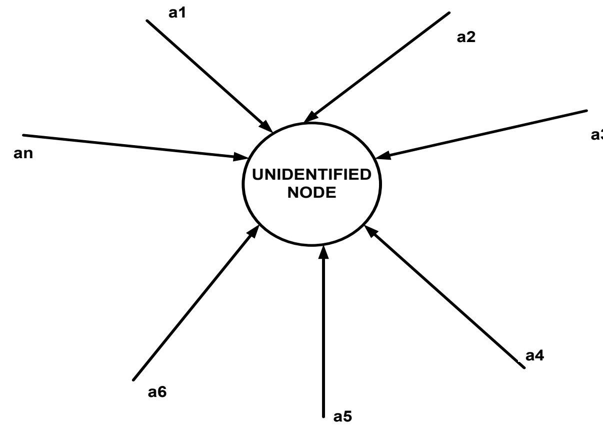

Figure 2: Schematic diagram of multilateration

D. Linear Intersection Formulation

Linear Intersection Formulation is an effective approach used for engineering surveying. The objective of this approach is to handle the point's densification. For example 'X' and 'Y' are two control points shown in Figure 3 and their coordinates are (p_X, q_X) and (p_Y, q_Y). Assume that 'T' is the point whose locations are (p_T, q_T). We use simple and optimal computational formula to determine the accuracy of the location.

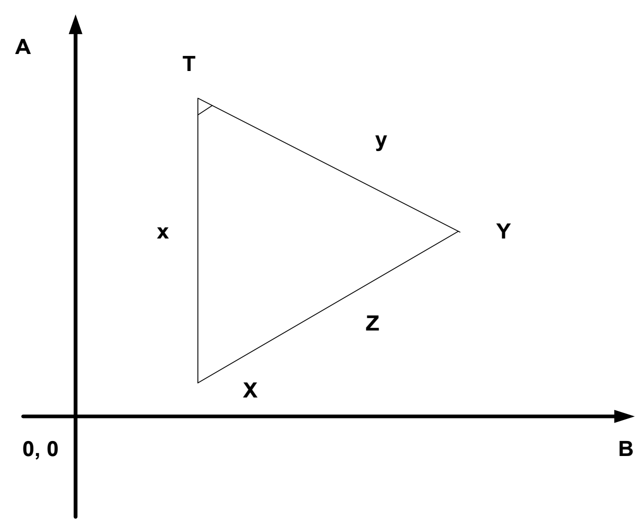

Figure 3: showing linear intersection

Let us compute the distance between 'X' and 'Y' and their respective coordinates that is illustrated as follows:

$$Z = \sqrt{(p_X - p_Y)^2 + (q_X - q_Y)^2} \tag{7}$$

The equation (7) can be expressed as:

$$\begin{cases} p_T = p_X + \; Length(p_Y - p_X) + Height\,(q_Y - q_X) \\ q_T = q_X + \; Length(q_Y - q_X) + Height\,(p_Y - p_X) \end{cases} \tag{8}$$

$$\begin{cases} Length = \dfrac{x^2 + Z^2 - y^2}{2Z^2} \\ Height = \sqrt{\dfrac{x^2}{Z^2} - (Length)^2} \end{cases} \quad (9)$$

The above model is convenient and simple and fit for measuring computation power of sensor nodes while finding the location of the unidentified node.

III. Simulation Setup

The performance of optimized cooperative scheduled based localization (OCSL) is evaluated through extensive simulations. We analyzed the projected location of nodes with their real locations and investigated the disturbing factors. We assume that unidentified and beacon nodes are located at the same plane.

For the situation of randomly organized nodes and beacons, we run a simulation to confine 15 nodes using 150 particles and 15 beacons in a 1200 × 1200 square meter area. The approximation error of each node particle can be found. It is also noticed that the location appraisals for all nodes get stable after six iterations using 15 beacons. In addition, we examine the liaison between the number of particles and estimation errors. Due to the random deployment, we run each trial 12 times and calculate the statistical data.

We obtain the localizing error when using a different number of particles to analyze the mixed behavior. We noticed that the approximation error becomes lower while aggregating the particle number. The remaining simulation parameters are given in Table 1.

Table 1: Simulation parameters

PARAMTERS	VALUE
Size of WSN	1200 × 1200 square meters
Number of particles	480
Number of beacons	15
Medium Access Control Protocol	IEEE802.14
Transport layer Protocol	TCP and UDP
Application Layer Protocol	FTP and HTTP
Mobility Model	Random-way mobility model
Transmission Range	30
Size of Packets	128 bytes
Data Rate	260 kilobytes/second
Time for topology change	1 seconds
Sensing Range of node	10 meters
Initial energy of node	4 Joules
Bandwidth of node	30 kilobytes/second
Simulation time	10 minutes
Average Simulation Run	15

A. Estimation Errors

Most of the scheduled based localization algorithms use iterative weighted least squares method but our algorithm use trilateration, multilateration and linear intersection. The least squares problems have been investigated extensively. We considered 15 unidentified nodes and varying number of beacons, which are randomly located in 1200X1200 square meters.

The transmission power is initially set globally at the maximum level. We compared the variation beacon-effect from accuracy point of view. For each scenario, we counted an average of 12 simulation runs with different types of randomly generated network topologies. The accuracy outcomes are shown in Figure 4. It is observed that increasing the beacon density, makes the localization more effective. Furthermore, we also compared the performance of DDBMS with our proposed approach in the context of four power levels, as presented with the lower two curves in Figure 5. The rest of the parameters of both approaches are the similar as in the case of a single power level.

Our proposed approach efficiently improves the estimation accuracy and latency remarkably degrades the localization accuracy particularly for moving sensor nodes in DDBMS approach. The processing time of our approach does not significantly affect the performance during the mobility while DDBMS affects the performance. In addition, longer process time makes our approach stable as DDBMS not only consumes more power but also leads to longer delay.

A. Computational complexity

The computation time increases when the number of nodes increases. By restraining the node density with our approach, we bound our approach with computation time that increases the rate at which an exact result is obtained. In the case of mobile nodes, convergence latency is of paramount importance, as slow locations are computed. As a result, the error is increased. By limiting the node density in an organized manner, we use less information to compute the node location. Therefore, determining the current location of the node using limited distance and location measurements decreases the computation time.

We use trilateration and multilateration computation with different node densities on different mobility rates. The system clock evaluations with microsecond correctness were obtained before and after the localization processes. In Figure 6 and 7, we show the average computational time on different mobility rates.

B. Energy Consumption and Error Tolerance

In this experiment, we show the tradeoff relations between error tolerance and energy consumption using our proposed method and three existing approaches: CALL, MEACL and DDBMS. Figures 8-10 shows four energy curves with 25%, 50% and 75%. CALL has the worst performance, followed by MEACL and DDBMS. At the 25% mobility level shown in Figure 8, our approach outperforms CALL and MEACL by 12.5-15%% and 19.4-21% at the rate 6 and 12 meters error tolerance respectively. It also outperforms DDBMS by 7.4% and 10.2% at 6 and 12 at error tolerance respectively. In Figure 9, our approach outperforms CALL and MEAC by 8.5-11.5% and 16.5-18.2% at the rate 6 and 12 meters error tolerance respectively. It also outperforms DDBMS by 6.2% and 9% at 6 and 12 at error tolerance. In Figure 10, our approach outperforms CALL and MEAC by 6-8.9% and 12.5-16% at the rate 6 and 12 meters error tolerance respectively. It also outperforms DDBMS by 5% and 7.5% at 6 and 12 at error tolerance.

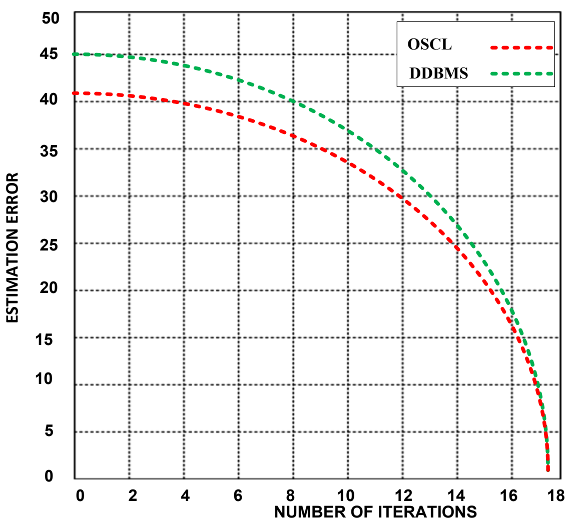

Figure 4: Estimation error versus iterations at 12 beacon nodes, 10 power levels, and 2 unidentified nodes

IV. Discussion and Results

The node localization has been known as one of the highest challenges in wireless sensor networks. This challenge has fascinated researchers to present several new localization protocols to address this issue. In this section, we discuss and compare the benefits and weakness of OCSL and other scheduled based localization approaches. PF yields a subsequent trust of the node location through a series of prediction and resampling processes. However, the predication cannot be accurate in some circumstances. As a result, a sensor might measure the location of a wrong node and thus wastes energy.

SEMP involves using additional sensor nodes to estimate the mobility parameters of moving targets which involves additional hardware.

SSEEL controls the wake-up issue; multiple nodes are used concurrently to become references. Furthermore, entitled nodes wait for randomized delay before broadcasting their decision to their neighbor nodes. SSEEL does not have mobility support.

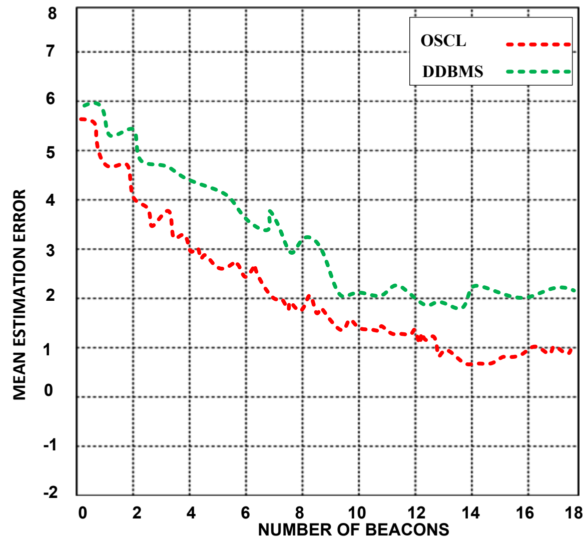

Figure: 5 Effect of the beacon number on localization accuracy

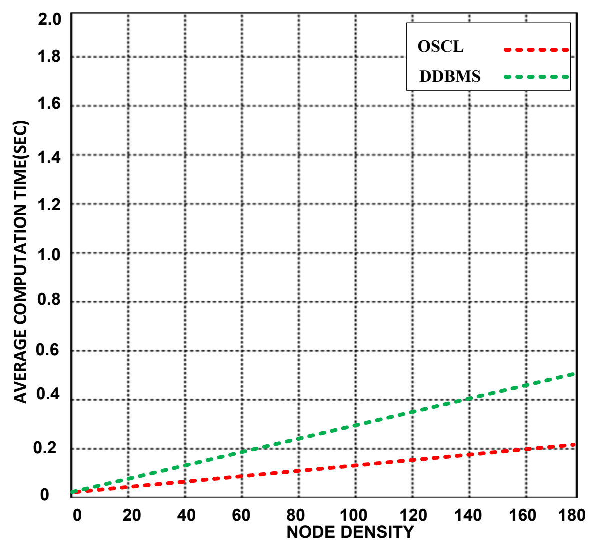

Figure 6: Average computation and node density of nodes

CALL determines all the globally rigid parts during component generation process. However, identifying all the globally inelastic parts is computationally exhaustive. The disadvantage of this scheme is that it consumes additional energy.

MEACL approach does not need explicit time synchronization among the candidate relays but they are implicitly synchronized while using beacon message. However, the relay selection process can be unsuccessful due to the receive-to-transmit switch time and existence of propagation delay.

DDBMS ensure the complete localization and suggests using topology control and node elimination for reduction of the delay. However, it experiences problems with mobile targets and produces more errors.

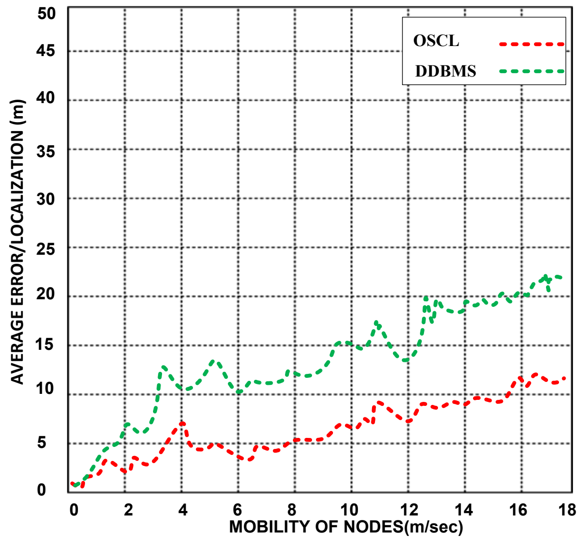

Figure 7: Localization error with respect to different mobility rates

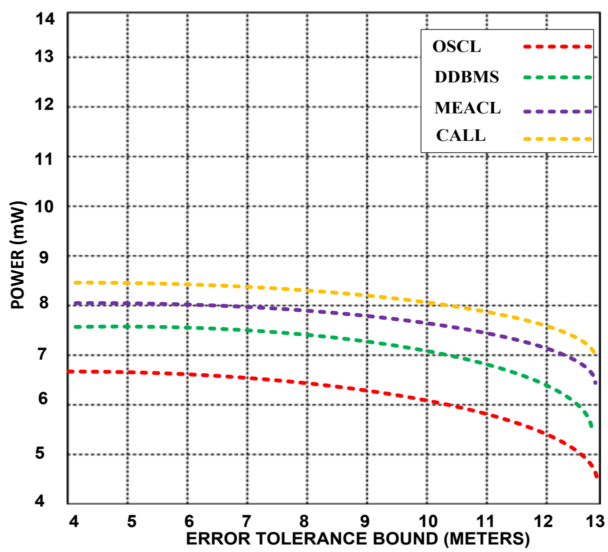

Figure 8: Tradeoff between power consumption and error tolerance under 75% mobility rates

Our proposed OCSL is energy efficient, accurate and specially designed to support air- traffic control. OCSL is based on literation, multileteration and linear intersections. These characteristics make it highly robust for determining the location of the nodes as faster as compared with other approaches. In addition, our approach produces fewer errors under different mobility rates. A comparison of OSCL versus existing approaches is given in Table 2.

V. Conclusions

In this paper, we introduced optimized cooperative scheduled based localization technique for wireless sensor networks. Based on trilateration, multilateration and linear intersection, we have demonstrated the necessary conditions for this approach. As a result, we estimated the soundness of the model through tangible experiments. The simulations results demonstrate that the cooperative scheduled based localization model is predominantly determined through distance measurement accuracy.

This approach has edge in WSNs over all the existing approaches as it is based on very simple model with minimum communication overhead. However, few of its special features may limit its application especially in disaster situation using linear intersection. These limitations can be handled using trilateration and multilateration. In the future we plan to implement some of the related approaches of scheduled based WSN localization such as distance measurement approaches which can lead to substantial improvement and deliver a better accuracy and error free localization.

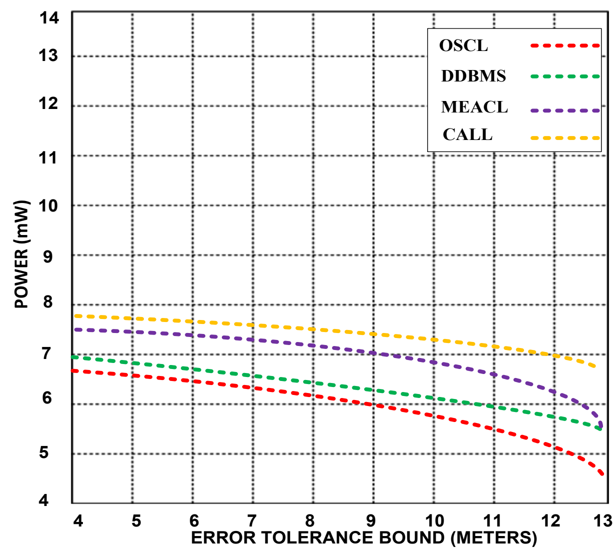

Figure 9: Tradeoff between power consumption and error tolerance under 50% mobility rates

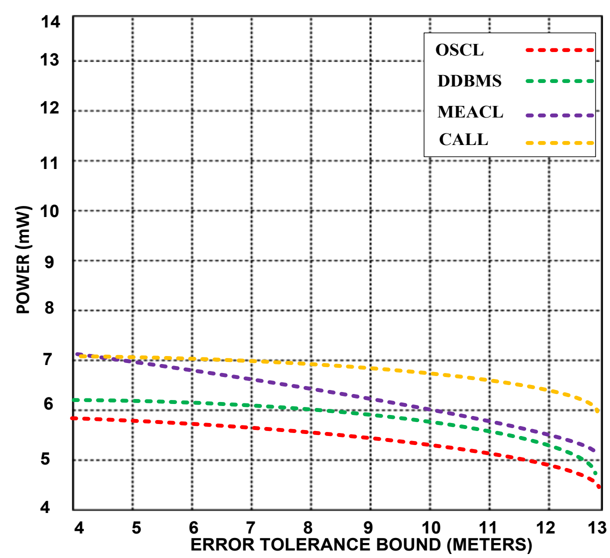

Figure 10: Tradeoff between power consumption and error tolerance under 25% mobility rates

Table 2: Characteristics of scheduled based cooperative approaches

Parameters	**PF**	**SEMP**	**SSEEL**	**CALL**	**MEACL**	**DDBMS**	**Proposed OCSL**
Accuracy	Low	Low	Low	Low	Low	Low	High
Power Consumption	Median	Low	Low	Low	Median	Median	Low
Mobility	No	No	Marginal	Marginal	No	No	Yes
Node Density	High	High	Median	Median	Low	Median	High
Computation cost	Median	Median	Median	Low	Median	Low	Low
Position Error	2.8%	3.01%	3.1%	2.76%	2.45%	2.38%	1.2%
Hardware Cost	Median	Low	High	Median	Low	Median	Low
Beacon Percentage	18	18	22	16	17	16	15
Error Propagation	2.3%	2.05%	2.15%	2.005%	1.94%	1.007%	0.24%
Communication Cost	Median	Low	Median	Median	Low	High	Low
The degree of irregularity (DOI)	0.07	0.055	0.08	0.095	0.058	0.092	0.0012

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